Auditory Features Analysis for BIC-based Audio Segmentation

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Abstract: Audio segmentation is one of the stages in audio processing chain whose accuracy plays a primary role in the final performance of the audio recognition and processing tasks. This paper presents an analysis of auditory features for audio segmentation. A set of features is derived from a time-frequency representation of an input signal and has been calculated based on properties of human auditory system. An analysis of several sets of audio features efficiency for BIC-based audio segmentation has been performed. The obtained results show that auditory features derived from different frequency scales are competitive to the widely used MFCC feature in terms of accuracy and the number of detected points.

1 INTRODUCTION

An accurate determination of audio segment boundaries has important influence on the efficacy of numerous audio and speech processing tasks. As a result of the segmentation stage, an input audio stream is decomposed into slices with determined positions where audio content has a different acoustical structure. The process of audio segmentation employs the properties of feature space obtained in the audio parametrization stage.

The typical approaches for segmentation of acoustical data can be categorized into two main groups: metric-based and model-based. The first group includes techniques based on the distance measures between adjacent audio frames to evaluate acoustic similarity and to determine boundaries of the segments.

Another group contains methods for data models comparison. The most popular technique is based on the model analysis approach where the maximum likelihood is estimated and the decision of a change is made using the Bayesian information criterion (BIC) (Chen and Gopalakrishnan, 1998). Although this method gives good performance in many segmentation systems, model-selection algorithms have rather high computational cost (Cheng and Wang, 2003). Additionally, the effectiveness of this segmentation approach is dependent on the analysis window selection and computational decomposition. Several techniques to deal with these issues are presented in (Cettolo and Vescovi, 2003) and (Cheng et al., 2008).

Other approach to audio stream segmentation is a technique which exploits self-similarity decomposition (Foote and Cooper, 2003). Such decomposition is performed by calculating an audio inter-frame spectral similarity in order to create a similarity matrix. The audio segment boundaries are calculated by correlating the diagonal of the similarity matrix with a dedicated kernel. The obtained correlation result represents the possible boundaries of the audio regions.

An accuracy of audio segmentation algorithms depends on the properties of feature space: its dimensionality and the type of acoustical features. Moreover, the accuracy may be improved by limiting the number of possible acoustical groups and performing the segmentation process for specialized tasks like speaker diarization, broadcast news segmentation, speech/music regions determination, etc.

Also, the important factors diminishing the segmentation effectiveness for speech signals are the acquisition conditions. In order to reduce the influence of adverse conditions on a particular segmentation task, the robustness of features to noise should be guaranteed. The compensation of the background noise influence on the segmentation process may be performed by using background models in the channel variability reduction process. For example, in (Castan et al., 2013) a system based on segmentation-by-classification approach using the compensation channel variability between the input signal and acoustical background has been presented.

The main goal of this paper is the analysis and se-

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lection of the most discriminative audio features for model-based audio segmentation. The paper is organized as follows. Section 2 describes auditory features exploited in analysis. In Section 3 the well-known technique called ΔBIC based on model analysis for audio segmentation is presented. Section 3 contains experimental results and discussion. The last section concludes with the summary.

2 AUDIO FEATURES

In order to perform the audio segmentation phase, a set of features describing the properties of signal changing significantly between two different segments is required. Typically, in the majority of audio segmentation systems the mel-frequency cepstral coefficients (MFCC) are used (Wu and Hsieh, 2006; Xue et al., 2010; Chen and Gopalakrishnan, 1998). Because the feature space type determines the segmentation performance, we have decided to perform the feature space analysis for different popular and new feature sets.

In our study, the set of features includes typical descriptors like LFCC and LPC which are exploited in speech analysis and recognition tasks (Rabiner and Schafer, 2010). Furthermore, we have introduced the BFB feature set, where we used the set of 24 band-pass filters mapped onto the Bark scale (Smith, 2011). Then for each filter output, an energy was computed and used as a descriptor. As it was reported in (Shao and Wang, 2009), the GFCC features outperforms the MFCC features for speech recorded in adverse conditions. Therefore, we have decided to include it in our study. For the final feature set we have proposed several simple descriptors using auditory filter bank. These features are based on signals obtained from the filter output such as Hilbert envelope, instantaneous phase and frequency. For these signals we have measured period, mean, standard deviation and maximum values.

The process of auditory features extraction uses the approach presented in (Wang and Brown, 2006), where an input signal is decomposed into a set of auditory channels using the bank of filters derived from observation of an auditory periphery. The usage of auditory filter bank is motivated by its robustness in comparison to Fourier-based analysis for signals with mixtures of different sound sources (Ghitza, 1994). The auditory filter called gammatone has been designed based on functional approach of basilar membrane mechanics.

The gammatone filter is a bandpass filter with the following impulse response (Cooke, 2005):

$$g(t) = t^{n-1} \cdot e^{-b\cdot t} \cdot e^{i\cdot 2\cdot\pi\cdot f_c\cdot t}, \tag{1}$$

where: n is the filter order, b denotes bandwidth for a given frequency using equivalent rectangular bandwidth (ERB) and f_c is the filter center frequency.

Assuming that $m(t)$ represents the complex output of an auditory filter at frequency f_c, we have computed the instantaneous phase $\varphi(t)$, instantaneous frequency $f(t)$ and Hilbert envelope $H(t)$ as follows:

$$\varphi(t) = \arg[m(t)], \tag{2}$$

$$f(t) = \frac{1}{2\pi} \cdot \frac{d}{dt}\, \varphi(t), \tag{3}$$

$$H(t) = |m(t)|. \tag{4}$$

Having obtained signals $\varphi(t)$, $f(t)$ and $H(t)$ we have calculated features 7–12 presented in Tab. 1. In case of the GTACI feature, we have estimated the period of the filtered signal using a common approach exploiting autocorrelation function and peak detector (Rabiner and Schafer, 2010).

Table 1: Feature sets used in the experiments.

#	Feature	Description
1	MFCC	Mel frequency cepstral coefficients (Rabiner and Schafer, 2010)
2	BFB	Bark frequency filter bank (Smith, 2011)
3	LFCC	Linear frequency cepstral coefficients (Rabiner and Schafer, 2010)
4	LPC	Linear prediction coefficients (Rabiner and Schafer, 2010)
5	GFCC	Gammatone frequency cepstral coefficients (Shao and Wang, 2009)
6	GTACI	Autocorrelation-based period estimator of filter output
7	GTFMN	Mean of $f(t)$
8	GTFSD	Standard deviation of $f(t)$
9	GTPMN	Mean of $\varphi(t)$
10	GTPSD	Standard deviation of $\varphi(t)$
11	GTPMX	$\max[\varphi(t)]$
12	GTEMX	$\max[H(t)]$

3 CHANGE POINT DETECTION

One of the most popular techniques for audio segmentation called Delta-BIC is based on the approach presented in (Chen and Gopalakrishnan, 1998), where the acoustic change detection uses the Bayesian information criterion (BIC) model selection penalized by the model complexity. The delta-BIC method compares two models: a model with data coming from a single Gaussian distribution $N(\mu,\Sigma)$ and with data modeled by two Gaussians – $N(\mu_1,\Sigma_1)$ and $N(\mu_2,\Sigma_2)$. The data for the second model is extracted by splitting the input data at specified position i to the left and right-side windows as depicted in Fig. 1.

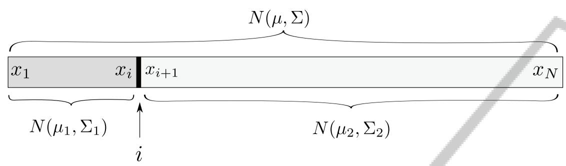


Figure 1: Data split in Delta-BIC segmentation scheme.

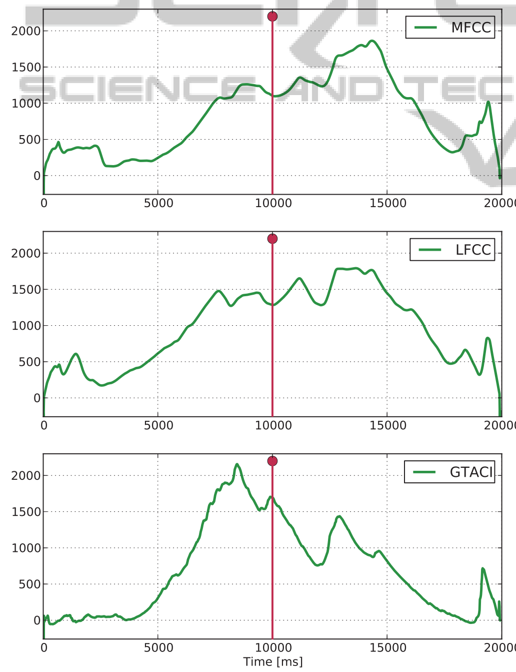


Figure 2: Delta-BIC trajectories calculated for the 6th dimensional feature space ($d = 6$) of the following features (from top to bottom): MFCC, LFCC and GTACI.

The ΔBIC trajectory is computed as:

$$\Delta BIC(i) = N_1^{(i)} \log\left|\Sigma_1^{(i)}\right| - N_2^{(i)} \log\left|\Sigma_2^{(i)}\right| - N \log|\Sigma| - \frac{\lambda \cdot \log N \cdot d(d+3)}{4}, \quad (5)$$

where: N is the total length of analysed data window $\{x_1,\ldots,x_N\}$, $N_1^{(i)}$ - the size of the left-side window $\{x_1,\ldots,x_i\}$; $N_2^{(i)}$ - the size of the right-side window $\{x_{i+1},\ldots,x_N\}$; $\left|\Sigma_1^{(i)}\right|$, $\left|\Sigma_2^{(i)}\right|$ and $\left|\Sigma^{(i)}\right|$ are determinants of covariance matrices for the left-side, right-side and the whole window; λ is a penalty weight and d is a dimension of the feature space. Example Delta-BIC trajectories for three different features are depicted in Fig. 2. As it can be noticed, the type of feature space is directly connected with the position of the maximum value and thus it describes the occurrence of the change point. The maximum value of $\Delta BIC(i)$ determines a possible change point at position $\arg\max_i \Delta BIC(i)$ when inequality $\max_i \Delta BIC(i) > 0$ is satisfied.

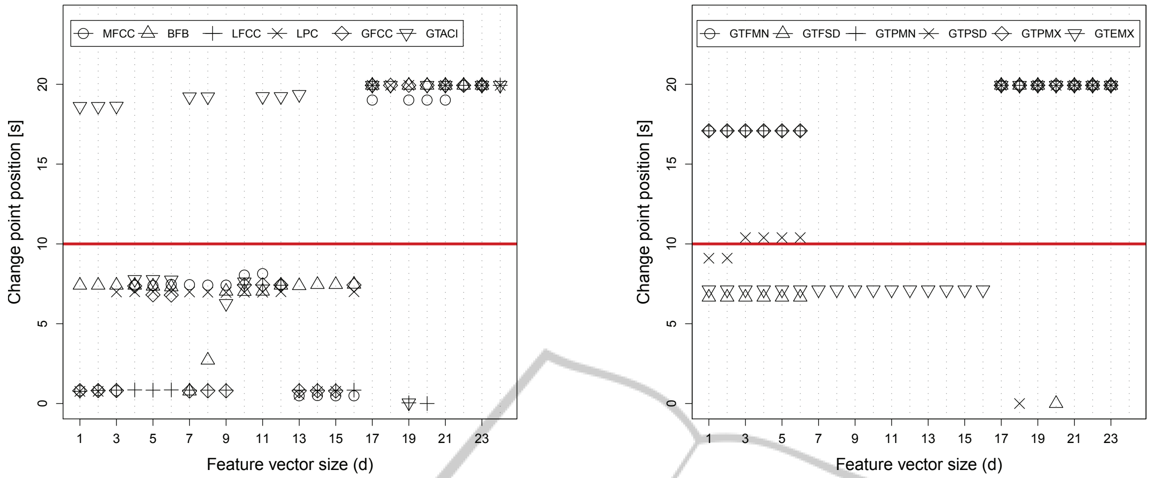
4 EXPERIMENTAL EVALUATION

The main purpose of the experiments was to determine which feature set gives the best results in detecting a single change point in one audio data window using an analysis of ΔBIC trajectory. Thus, we have used manually marked boundaries in broadcast news database (Garofolo et al., 2004) as reference points for segmentation. The characteristics of existing change points in available recordings from the database is provided in Tab. 2.

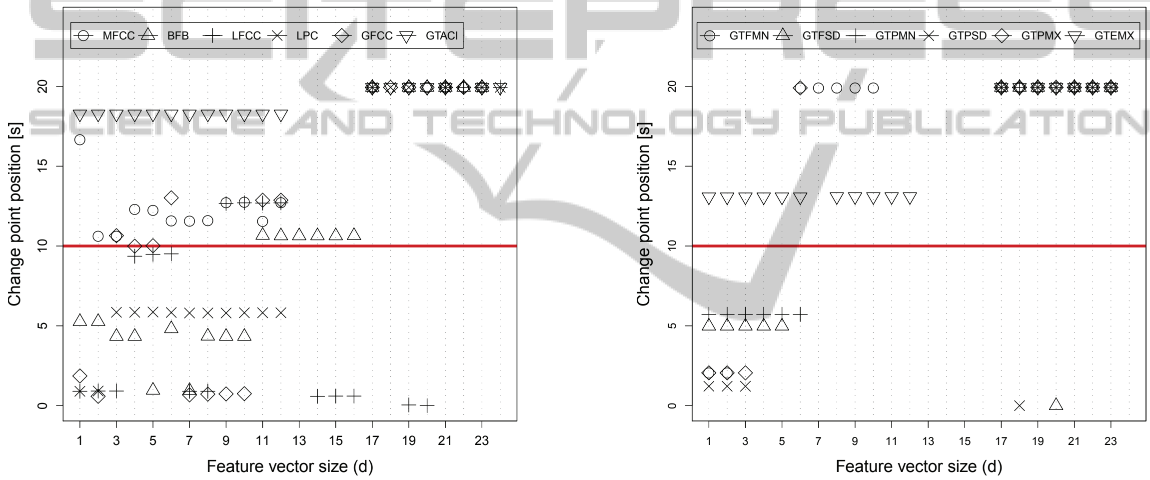
Table 2: Types of segment boundaries in database (M/F – Male/Female speech).

#	Boundary type	Occur.
1	music ↔ (M, F) / clean	10.9 %
2	(M, F) / clean ↔ (M, F) / mixture	5.7 %
3	(M) / clean ↔ (M) / clean	17.1 %
4	(F) / clean ↔ (M) / clean	20.6 %
5	(M) / clean ↔ (M, F) / noise	25.7 %
6	(F) / clean ↔ (M) / noise	4 %
7	(M) / noise ↔ (M, F) / noise	16 %

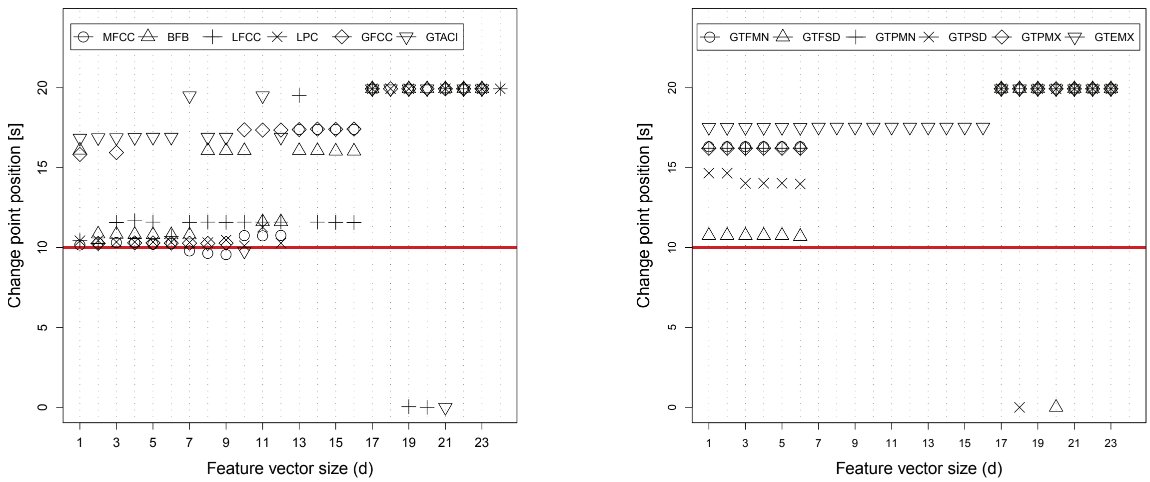
The prepared recordings in data set have length 20s, with one defined change point after 10 second each. The selected audio data had the sampling rate 22.5kHz/mono and the feature extraction process has been done using a frame length equal to 30ms with 50% overlapping. In our experiments we have used $n = 4$ order of the gammatone filter (Eq. 1) for auditory features calculation and the penalty weight $\lambda = 1$ (Eq. 5) in the segmentation stage. We have performed the experiment where all feature sets (Tab. 1) have been used to calculate ΔBIC and to detect the segment boundary. We have changed the number of features in a single set from 1 to 24 and determined the position of the change point. Due to the same length of each audio example, the change



(a)



(b)



(c)

Figure 3: Positions of detected change points using all features for three example segments: speech (M) / clean $\rightarrow$ speech (M) / clean (a), speech (M) / clean $\rightarrow$ speech (F) / noise (b) and speech (F) / clean $\rightarrow$ speech (M) / clean (c).

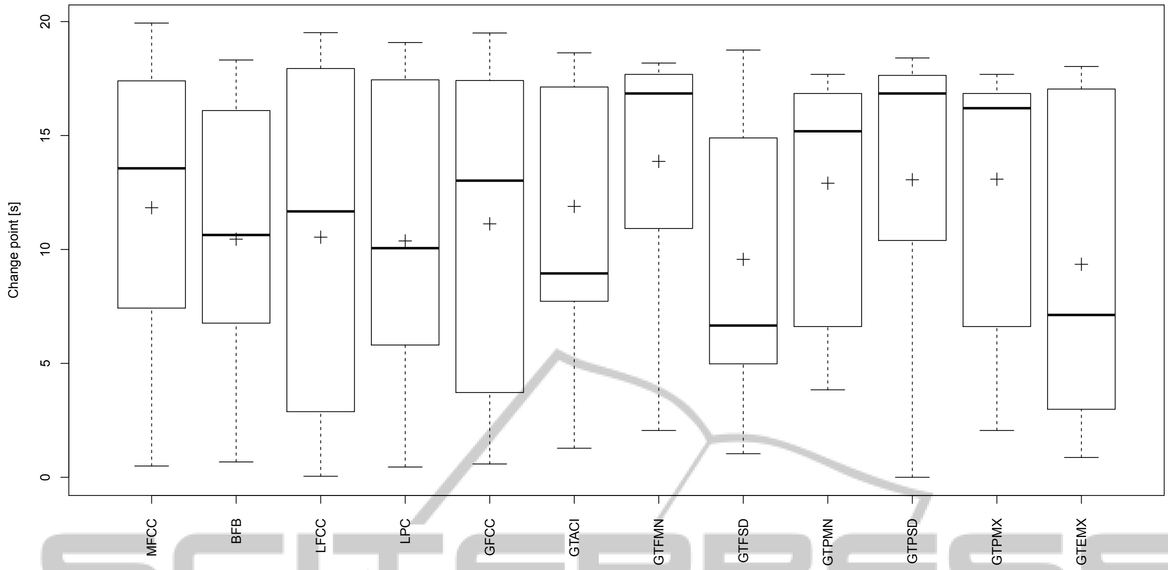


Figure 4: Distribution of detected positions between two segments for the whole analysed data.

point should occur at the same position in each case. The obtained results for three examples are shown in Fig. 3, where the horizontal line denotes the defined change point. The best accuracy of the detected points for the first example (Fig. 3a) has been obtained for GTPSD ($d = 3,4,5,6$), second example (Fig. 3b) has been observed for GFCC ($d = 4,5$) and in the last case (Fig 3c) for MFCC, LPC, LFCC and GFCC ($d = 1,\ldots,12$). In case of all the examples, the statistics of the detection accuracy are presented in Fig. 4 where the cross symbol denotes the arithmetic mean.

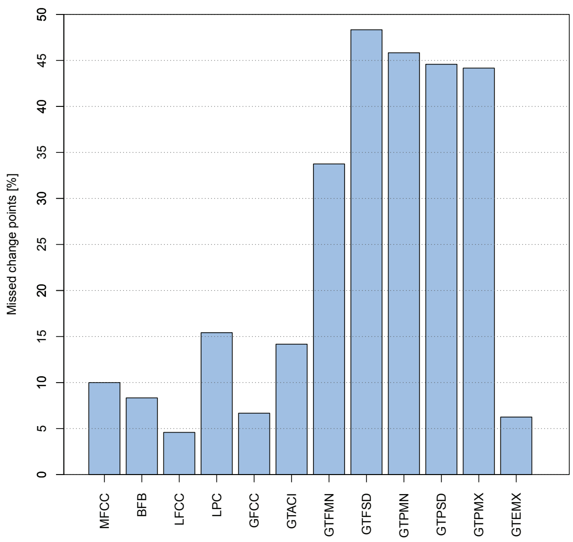


Figure 5: The percentage of missed change points for each set of features.

As a quality indicator of the differences between positions of change points, the mean square error has been used. In Fig. 6 the mean squared errors for change point at position equal to 10 second are depicted. In this case, the best and the worst results have been obtained for BFB and GTPSD features, respectively.

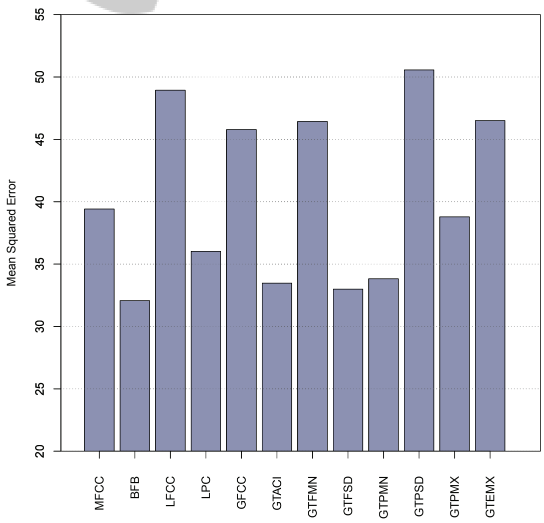


Figure 6: Total mean square error of the positions of the change points for each tested feature.

As it can be seen, for features BFB, LFCC, LPC, GTFSD and GTEMX, the mean value is close (less than 3 seconds) to the actual change point. For that reason the feature space for ΔBIC trajectory calculation should include a combination of such features. In many cases change points have not been detected.

Therefore, we have counted such cases and the result is depicted in Fig. 5. The worst efficiency in terms of missed change points has been observed for features 7–11 (Tab. 1). The features exploited in our study represents the properties of frequency distribution of the input signals at different frequency scales. Consequently, due to the fact that the input data in our study contains mostly speech, the features which exhibit the variability details of speech signal have led to the most promising results.

In the most cases the fact of change point detection is more important than the obtained accuracy. Thus, the selection of feature vector size together with the selection of the feature type is significant for the final performance of the segmentation process. Also, the parametrization stage should be carefully configured for the expected types of audio segments and the target application.

5 CONCLUSIONS

In this paper an analysis of auditory features efficiency for BIC-based audio segmentation has been performed. For several examples 12 feature sets have been examined. As the result, the features BFB, LFCC, GFCC, GTACI and the GTEMX give promising results and they are competitive to the MFCC feature widely used in many audio segmentation systems. Due to the variability of the content in segment boundaries, better results seem to be achieved in case of using joint different features. Also, in typical segmentation algorithm, an analysis window selection and moving strategy have an important influence on the segmentation results. Furthermore, the fusion and clustering methods of the obtained change points may improve significantly the result for signals with several audio classes. Finally, an analysis of features based on cochleagram and correlogram with generalized likelihood ratio (GLR) and Hotteling's T^2 trajectories is the future subject.

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